The IBM Quantum Computing Challenge Lab 0 | Lab 1

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What is the IBM Quantum Computing Challenge

“Welcome to the IBM Quantum Challenge, the annual code challenge focused on how to use Qiskit. Whether you’re a newcomer or a seasoned veteran, there is something here for you.

The Quantum Challenge consists of a series of Jupyter notebooks that contain tutorial material, code examples, and auto-graded coding challenges for you to fill in. We call each of these notebooks a ‘lab’. “

Lab 0: Overview

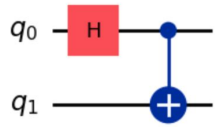
The workflow of Qiskit pattern: Set up, Optimize, Run, and Process your circuit.

Create a two-qubit Bell state and show that it is properly entangled by visualizing the operators.

Step 1: Map our Circuits and Operators

Circuit

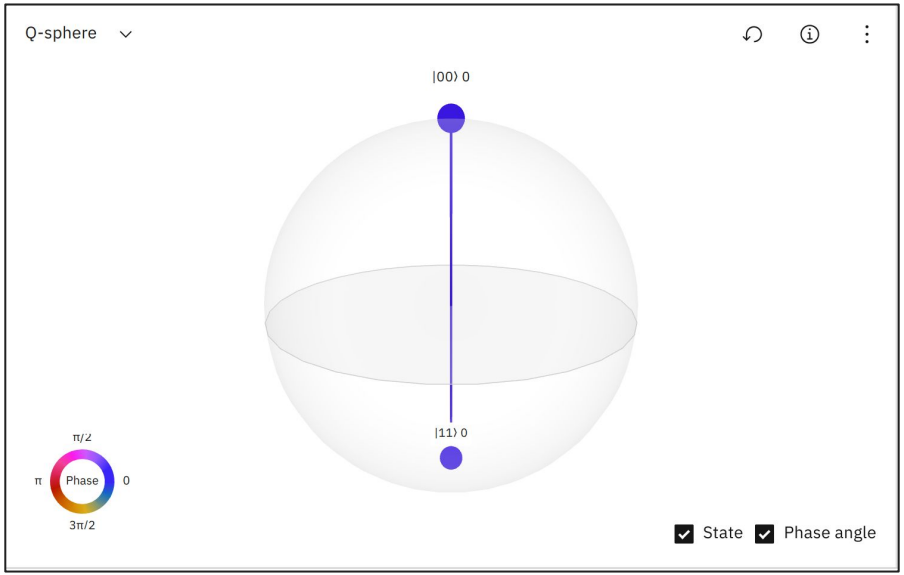
```
# Create a new circuit with two qubits
qc = QuantumCircuit(2)

# Add a Hadamard gate to qubit 0
qc.h(0)

# Perform a CNOT gate on qubit 1, controlled by qubit 0
qc.cx(0, 1)

# Return a drawing of the circuit using MatPlotLib ("mpl"). This is the
# last line of the cell, so the drawing appears in the cell output.
qc.draw("mpl")
```



Operators

```
# The ZZ applies a Z operator on qubit 0, and a Z operator on qubit 1
ZZ = SparsePauliOp('ZZ')

# The ZI applies a Z operator on qubit 0, and an Identity operator on qubit 1
ZI = SparsePauliOp('ZI')

# The IX applies an Identity operator on qubit 0, and an X operator on qubit 1
IX = SparsePauliOp('IX')



### Write your code below here ###

IZ = SparsePauliOp('IZ')

XX = SparsePauliOp('XX')

XI = SparsePauliOp('XI')
### Follow the same naming convention we used above



## Don't change any code past this line, but remember to run the cell.

observables = [IZ, IX, ZI, XI, ZZ, XX]
```

Bell State



Step 2: Optimize

Optimization is done using transpliers.

They are able to reduce the number of gates required, and ensure the structure of gates will work on the machine being used.

Step 3: Execute

Estimator: A function (primitives) that estimates the output of a quantum circuit

Aer Simulator: A fake quantum computer backend

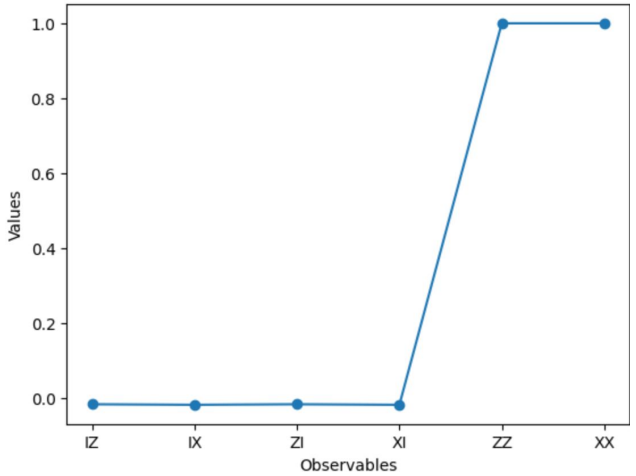
qc: Our quantum circuit

observables: Our operations to run on the circuit

```
[24] # Set up the Estimator
     estimator = Estimator(backend=AerSimulator())

     # Submit the circuit to Estimator
     pub = (qc, observables)

     job = estimator.run(pubs=[pub])
```

Step 4: Post Process the results

```
# Collect the data
data = ['IZ', 'IX', 'ZI', 'XI', 'ZZ', 'XX']
values = job.result()[0].data.evs

# Set up our graph
container = plt.plot(data, values, '-o')

# Label each axis
plt.xlabel('Observables')
plt.ylabel('Values')

# Draw the final graph
plt.show()
```



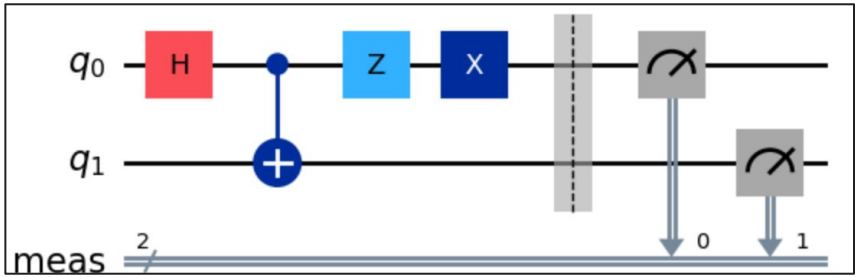
Lab 1: Overview

Qiskit states, the new and the old

VQE with Qiskit 1.0

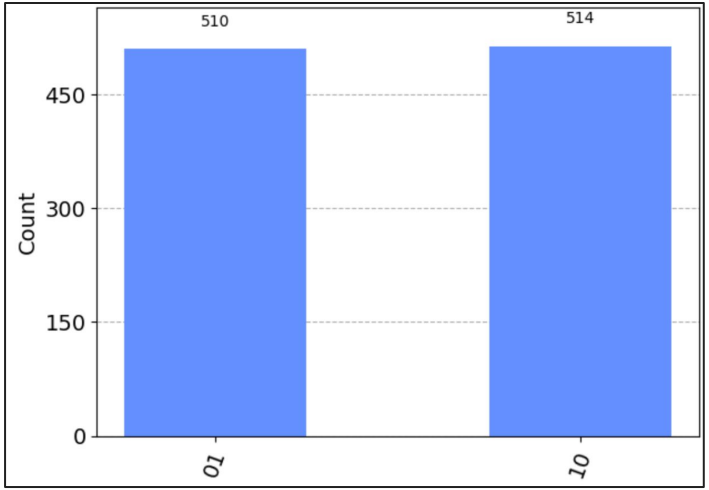
Step 1: Create and Draw a singlet Bell state Circuit

```
# Build a circuit to form a psi-minus Bell state
# Apply gates to the provided QuantumCircuit, qc

qc = QuantumCircuit(2)

### Write your code below here ###

qc.h(0)

qc.cx(0,1)

qc.z(0)

qc.x(0)



### Don't change any code past this line ###
qc.measure_all()
qc.draw('mpl')
```



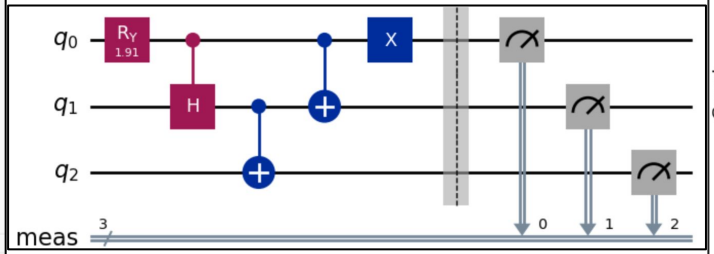
Step 2: Run it with Sampler

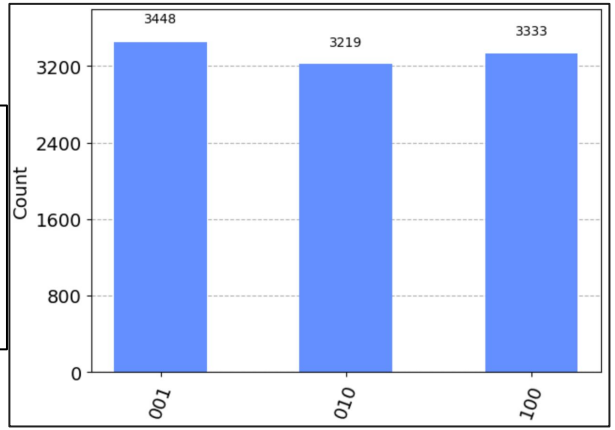
```
qc.measure_all()

### Write your code below here ###


sampler = StatevectorSampler()
pub = (qc)
job_sampler = sampler.run([pub])


### Don't change any code past this line ###

result_sampler = job_sampler.result()
counts_sampler = result_sampler[0].data.meas.get_counts()

print(counts_sampler)
```



Step 3: Create and draw a W-state circuit

```
# Step 1
qc = QuantumCircuit(3)

# Step 2 (provided)
qc.ry(1.91063324, 0)

# Add steps 3-6 below

qc.ch(0,1)

qc.cx(1,2)

qc.cx(0,1)

qc.x(0)

### Don't change any code past this line ###
qc.measure_all()
qc.draw('mpl')
```





Dive into VQE

VQE: Variational Quantum Eigensolver.

Executing a VQE algorithm requires these three steps:

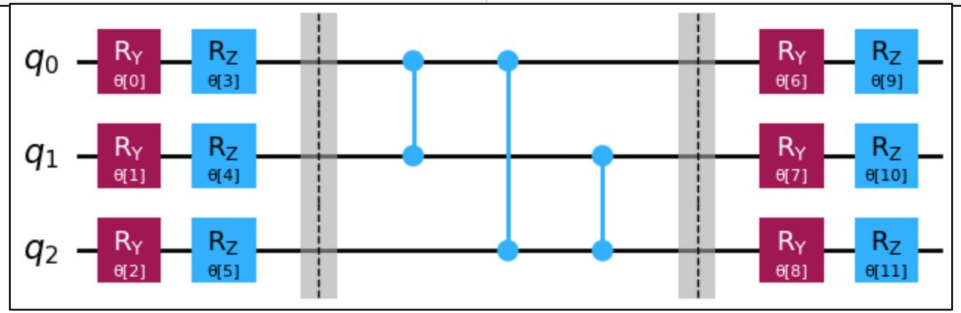
1. Setting up the Hamiltonian and ansatz (problem specification)
2. Implementing the Qiskit Runtime estimator
3. Adding the Classical optimizer and running our program

https://en.wikipedia.org/wiki/Variational_quantum_eigensolver

https://www.youtube.com/watch?v=TUFovZsBcW4

Step 1: Create a parameterized circuit to serve as the ansatz

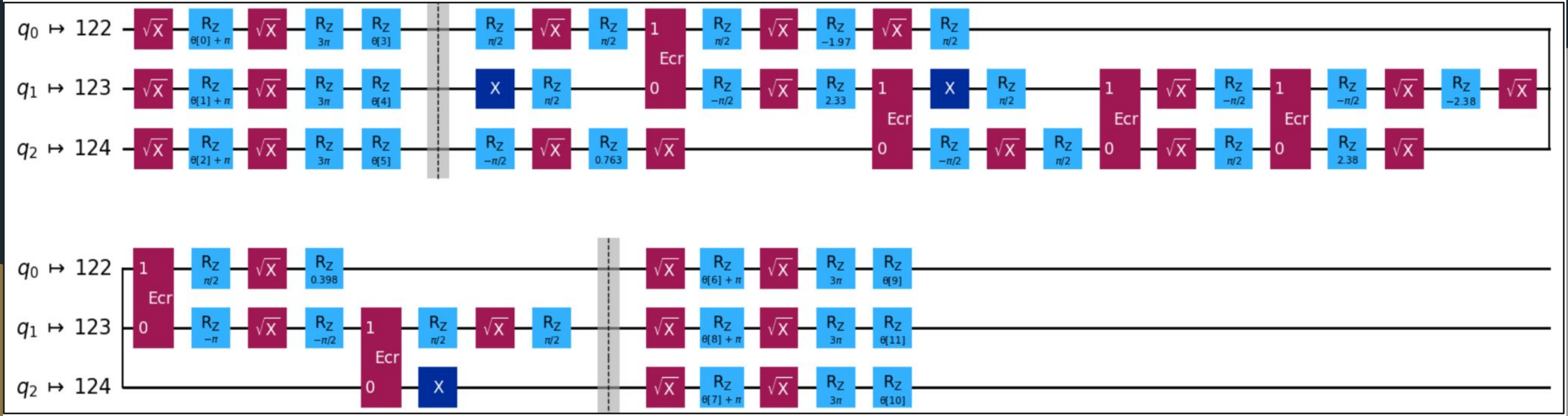
```
num_qubits = 3
rotation_blocks = ['ry','rz']
entanglement_blocks = 'cz'
entanglement = 'full'
reps = 1
insert_barriers=True
ansatz = TwoLocal(3,rotation_blocks=rotation_blocks, entanglement_blocks=entanglement_blocks,entanglement=entanglement,reps=reps,insert_barriers=insert_barriers)


### Don't change any code past this line ###
ansatz.decompose().draw('mpl')
```



Step 2: Transpile to ISA circuits

Instruction Set Architecture (ISA): The set of instructions the device can understand and execute.

```
backend_answer = FakeSherbrooke()
optimization_level_answer = 3
pm = generate_preset_pass_manager(backend=backend_answer,optimization_level=optimization_level_answer)
isa_circuit = pm.run(ansatz)
```



$q_0 \mapsto 122$: √X, Rz θ[0] + π, √X, Rz 3π, Rz θ[3], Rz π/2, √X, Rz π/2, Ecr, Rz π/2, √X, Rz −1.97, √X, Rz π/2
$q_1 \mapsto 123$: √X, Rz θ[1] + π, √X, Rz 3π, Rz θ[4], X, Rz π/2, Ecr, Rz −π/2, √X, Rz 2.33, Ecr, X, Rz π/2, Ecr, √X, Rz −π/2, Ecr, Rz −π/2, √X, Rz −2.38, √X
$q_2 \mapsto 124$: √X, Rz θ[2] + π, √X, Rz 3π, Rz θ[5], Rz −π/2, √X, Rz 0.763, √X, Ecr, Rz −π/2, √X, Rz π/2, Ecr, √X, Rz π/2, Ecr, Rz 2.38, √X
$q_0 \mapsto 122$: Ecr, Rz π/2, √X, Rz 0.398, √X, Rz θ[6] + π, √X, Rz 3π, Rz θ[9]
$q_1 \mapsto 123$: Ecr, Rz −π, √X, Rz −π/2, Ecr, Rz π/2, √X, Rz π/2, √X, Rz θ[8] + π, √X, Rz 3π, Rz θ[11]
$q_2 \mapsto 124$: Ecr, X, √X, Rz θ[7] + π, √X, Rz 3π, Rz θ[10]

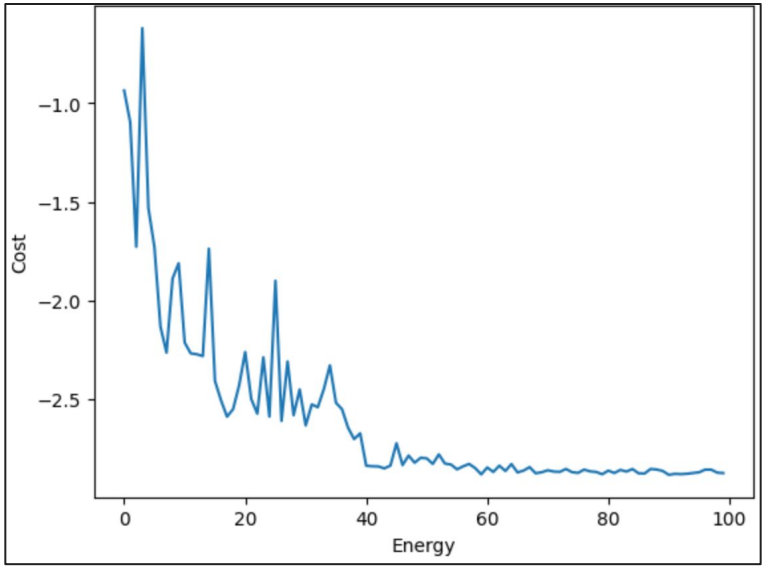
Step 3: Define a cost function

```
def cost_func(params, ansatz, hamiltonian, estimator, callback_dict):
    """Return estimate of energy from estimator

    Parameters:
        params (ndarray): Array of ansatz parameters
        ansatz (QuantumCircuit): Parameterized ansatz circuit
        hamiltonian (SparsePauliOp): Operator representation of Hamiltonian
        estimator (EstimatorV2): Estimator primitive instance

    Returns:
        float: Energy estimate
    """
    pub = (ansatz)
    result = estimator.run([(pub, hamiltonian, [params])]).result()
    energy = result[0].data.evs[0]

    callback_dict["iters"] += 1
    callback_dict["prev_vector"] = params
    callback_dict["cost_history"].append(energy)

### Don't change any code past this line ###
    print(energy)
    return energy, result
```

Step 4: Run it

```
] ### Select a Backend
  ## Use FakeSherbrooke to simulate with noise that matches closer to the real experiment. This will run slower.
  ## Use AerSimulator to simulate without noise to quickly iterate. This will run faster.

  # backend = FakeSherbrooke()
  backend = AerSimulator()

  # ### Don't change any code past this line ###

  # Here we have updated the cost function to return only the energy to be compatible with recent scipy versions (>=1.10)
  def cost_func_2(*args, **kwargs):
      energy, result = cost_func(*args, **kwargs)
      return energy

  with Session(backend=backend) as session:
      estimator = Estimator(session=session)

      res = minimize(
          cost_func_2,
          x0,
          args=(isa_circuit, hamiltonian_isa, estimator, callback_dict),
          method="cobyla",
          options={'maxiter': 100})
```

Data



Thank you!